Association for Information Systems
AIS Electronic Library (AISeL)

BLED 2020 Proceedings

BLED Proceedings

2020

The Data Product Canvas - A Visual Collaborative Tool for Designing Data-Driven Business Models

Michael Fruhwirth

Gert Breitfuss

Viktoria Pammer-Schindler

THE DATA PRODUCT CANVAS A VISUAL COLLABORATIVE TOOL FOR DESIGNING DATA-DRIVEN BUSINESS MODELS

MICHAEL FRUHWIRTH[1], GERT BREITFUSS[1] & VIKTORIA PAMMER-SCHINDLER[1,2]

[1] Know-Center GmbH, Graz, Austria, e-mail: mfruhwirth@know-center.at, gbreitfuss@know-center.at, vpammer@know-center.at
[2] Graz University of Technology, Graz, Austria, e-mail: viktoria.pammer-schindler@tugraz.at

Abstract The availability of data sources and advances in analytics and artificial intelligence offers the opportunity for organizations to develop new data-driven products, services and business models. Though, this process is challenging for traditional organizations, as it requires knowledge and collaboration from several disciplines such as data science, domain experts, or business perspective. Furthermore, it is challenging to craft a meaningful value proposition based on data; whereas existing research can provide little guidance. To overcome those challenges, we conducted a Design Science Research project to derive requirements from literature and a case study, develop a collaborative visual tool and evaluate it through several workshops with traditional organizations. This paper presents the Data Product Canvas, a tool connecting data sources with the user challenges and wishes through several intermediate steps. Thus, this paper contributes to the scientific body of knowledge on developing data-driven business models, products and services.

Keywords: data-driven business model, data product development, design-science research, visual collaborative tool, desisgning data.

University of Maribor Press

DOI https://doi.org/10.18690/978-961-286-362-3.35
ISBN 978-961-286-362-3

1 Introduction

The business models of many of today's most valuable firms, such as Google, Amazon, or Uber are heavily relying on data, analytics and artificial intelligence (Seibert and Gründinger, 2018). Likewise, data and analytics hold the potential for business model innovation in traditional organizations. But, "Much less has been written about how, exactly, companies should get started with [using artificial intelligence in business innovation]" (Agrawal et al., 2018).

Difficulties in developing data-driven services are the lack of a structured value proposition and a limited understanding of customer benefits inside the organization (Bertoncello et al., 2018). This means, before starting to develop data-driven offerings, organizations must identify a data product that meets a need from the market (Davenport and Kudyba, 2016). Furthermore, developing data-driven services is a collaborative task, involving knowledge and stakeholders from different disciplines such as data scientists, domain experts and business people. Currently, there are only a few data-focused tools and methods available to support the innovation process (Fruhwirth et al., 2020). Thus, we address the following research question in this paper: *How could a visual representation facilitate collaboration and idea generation for data-driven service ideas for non-data experts?*

In this paper, we propose the Data Product Canvas (DPC), a visual artifact that intends to support the process of developing a data-driven business model, and particularly considers the development of a structured value proposition, understanding of customer needs, and aims to support the necessary interdisciplinary communication. We have developed the DPC in a Design Science Research (DSR) process and present both its development and evaluation in the context of four workshops with practitioners from established organizations. In the evaluation, we studied the (perceived) usefulness and acceptance of the DPC, its actual usage as well as the generated outcome.

2 Conceptual Background

2.1 Data-Driven Business Models, Services and Products

The concept of a business model (BM) basically »describes the rationale how an organization creates, delivers and captures value« (Osterwalder and Pigneur, 2010, p. 14). Data is nowadays often used as a key resource in new BMs to deliver value to customers, so-called »data-driven business models« (Hartmann et al., 2016). One central dimension of a BM is the value proposition. Osterwalder and Pigneur (2010, p. 22) describe the value proposition as »the bundle of products and services that create value for a specific customer segment«. The focus of this BM element is how an organization satisfies customer needs, solves customer's problems, and shows what services and products are offered (Augenstein et al. 2018). The value proposition of a BM can be infused by data and analytics (Schüritz and Satzger, 2016), leading to new data-driven services. Data-driven services use »data and analytics to support the decision-making process of the customer via data and analytics-based features and experiences in form of a stand-alone offering or bundled with an existing product or service« (Schüritz et al., 2019, p.4). Chen et al. (2011) distinguish between two basic types of such service offerings: »Data-as-a-Service« and »Analytics-as-a-Service«. The former describes how data as an asset is offered, whereas the latter comprises offerings that enable customers to analyze large data sets. Next to data-driven services also the concept of »data products« emerged by practitioners (e.g., Glassberg Sands, 2018), as a subset of services. Specifically, data products help their users to make better decisions and formulate customer benefit (Tempich, 2019). The users of a data product can be internal or external customers. To deliver economic value for the product owner, a proper business model is required. The bottom line of those concepts, what we further refer to data products, is that data and analytics are used by a service provider to deliver value to a customer or data user (whereas the customer can be internal or external) to solve a customer problem, specifically supporting his decision-making process via a data product.

2.2 Collaborative Visual Tools for Designing Business Models

Individuals and organizations can be supported in the process of developing new business models through tools and methods (Schneider and Spieth, 2013). Visual tools help to communicate a firm's business model or stimulating collaborative innovation and idea generation (Osterwalder and Pigneur, 2010). There exist a variety of general tools, such as the Business Model Canvas (Osterwalder and Pigneur 2010). Furthermore, there exist also specialized representations for specific business model elements, such as the Value Proposition Canvas (Osterwalder et al., 2014) or specific types of business models (e.g., characterized through the type of key resource), supporting general representations of business models (Kühne and Böhmann, 2019). There is a lack of sufficient tools supporting the development of products and services based on data and analytics (Fruhwirth et al., 2020).

3 Method – Design Science Research

To develop the Data Product Canvas, we conducted a Design Science Research project to develop a new and innovative artifact that helps to solve the real-world problem of generating ideas for data products. We followed the iterative DSR process of Peffers et al. (2007) consisting of six phases as shown in Figure 1: problem identification and motivation; objectives of a solution; design and development; demonstration; evaluation; and communication. The introduction section of this paper addresses the »problem identification and motivation phase«. The second phase, »objectives of a solution«, consists of determining the requirements for developing data products from literature (Sect. 4). The third phase, »design and development«, focuses on how to transfer the requirements into a visual representation (Sec. 5). In the fourth phase of the DSR process, »demonstration«, we apply the developed representation within a pilot setting at a company to demonstrate its applicability (Sect. 4.1). In the fifth phase, »evaluation«, we evaluate the artifact for its usefulness and ease of use within workshops of different organizations (Sect. 6). The last phase »communication« is accomplished via this paper among others.

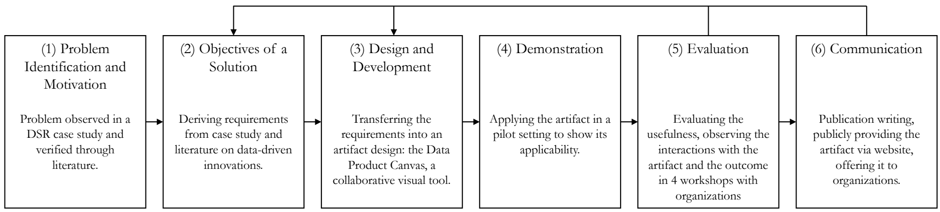

Figure 1: The DSR approach employed in this study (adapted from Peffers et al., 2007).

4 Requirements

4.1 Practical Requirements and Motivation

We have identified the problem within a broader DSR study (Fruhwirth et al., 2019) where the goal was to support a large automotive organization in innovating new data-driven business models. In this study, a one-day workshop with an external consultant organization and 12 participants, where two of the authors also participated, was conducted in 2018 to generate new business ideas based on data. Participants had positions in product management, research management or business development. We observed the need for a visual representation to structure and communicate data-related business ideas during the workshop. After three rounds of open ideation sessions with sticky notes, a generic template was used to further elaborate selected ideas in detail in small groups. The outcome of the workshop was a broad range of »digital business ideas«. Reflecting on the process and the outcome made it clear that especially traditional organizations that now want to go into the direction of data business need clear and structured guidance at the beginning of the innovation process to formulate and communicate business ideas with data. This observation served as the motivation and starting point for this research to develop a visual tool supporting idea generation. After the design phase, the tool was used to structure 21 data-related ideas from the case company. The analysis revealed that the user pains and benefits were not clear in most of the existing ideas, underpinning the need for such a collaborative visual tool supporting idea generation for data-driven services.

4.2 Theoretical Requirements for Developing Data-Driven Services

In order to elaborate design requirements for an artifact that aims to solve the problem of collaboratively developing ideas for data products, we reviewed existing literature on developing data-driven services, products and business models.

Identifying the required data sources is one crucial step within the exploration phase of data-driven innovations (Davenport and Kudyba, 2016; Kayser et al., 2019; Kronsbein and Mueller, 2019). Data can originate from different sources (e.g., internal information systems or free available sources (Hartmann et al., 2016)) or can be classified through different types (e.g. what the data is about (Hunke et al. 2019) or the format of the data (Kayser et al., 2019)). Beyond the diversity of data sources, there is also the challenge of insufficient shared data understanding within an organization when different roles and departments interact or work with the same data (Mathis and Köbler, 2016; Kayser et al., 2019). Making data visible is considered as one approach to address this issue to facilitate discussions for data-driven innovations (Kühne et al., 2019; Kayser et al., 2019). Thus, we frame the first design requirement (DR) for our artifact as follows: *DR-1: The necessary data sources for the data service should be visualized on a conceptual level to facilitate a shared understanding.*

Data itself often has no value for the user. Value is derived from data through the application of analytical methods to generate insights. There are different types of analytics methods for data products (Hunke et al., 2019); such methods can cluster, correlate, recommend, or search data to create meaningful insights that have potential value for data users. The organization should know which tools and methods are appropriate and necessary to generate insights from the data as well as how to interpret the data (Dremel et al., 2017; Kühne and Böhmann, 2019). Therefore, we articulate the second design requirement: *DR-2: The required data analytics methods and activities to generate insights from data should be visible in the artifact representation.*

The aim of using data and analytics by the service provider is to support the data users' decision-making process with the intent to create value for the customer (Schüritz et al., 2019). This means a proper fit between available data sources and user needs is vital for a compelling value proposition (Mathis and Köbler, 2016). Thus, beyond data analytics, data product development also requires customer intimacy and customer understanding (Wixom and Schüritz, 2017). Service design in general starts from the user perspective, meaning understanding the tasks (»job to be done«), challenges and wishes of the user and map them to the value offering (Osterwalder et al., 2014). Specifically, developing data products requires to bring together the business (customer understanding) and data world (Glassberg Sands, 2018; Mathis and Köbler, 2016) to create a meaningful solution. Thus, we articulate the third design requirement: *DR-3: The pains, wishes and needs of data users that could be addressed by the data product should be visualized to create a meaningful solution.*

The aim of designing data products is to solve the user's problems and address his wishes and needs. However, the provider alone is only creating potential value through the data service and the provider together with the customer is creating real value (Schüritz et al., 2019) through the usage of the data product in the decision-making process of the user. This relates to the concept, that information itself has no value; value results only from its usage (Moody and Walsh, 1999). As the user is at the center of the innovation process, the aspired value for the user should be described (Kronsbein and Mueller, 2019). To understand as an innovation team, how the data product creates what value for the customer through its usage, we articulate the fourth design requirement: *DR-4: The resulting value in use of the data product for the data user should be conceptualized.*

The development model of Davenport and Kudyba (2016) also covers the presentation of the data product. The presentation can have different forms, depending on the level of co-creation between provider and user: In the simplest form, a provider can deliver data through reports, dashboards or APIs, or in more sophisticated form through alerts or benchmarks or even automated decisions (Schüritz et al., 2019). A visual representation should also incorporate that view, i.e. to specify what is exchanged between the provider and the user. Thus, we articulate our fifth design requirement: *DR-5: The type of presentation of the data product should be visualized to conceptualize the data product.*

4.3 Existing Visual Representations for Developing Data Products

After deriving a set of requirements for an artifact that aims at providing a solution to the given problem, we check the requirements against existing visual representations to justify that there is an actual need for a new artifact. We conducted a structured literature review (Fruhwirth et al., 2020), to identify existing visual representations for data-driven innovations in the literature and added three more representations that were published after our search and selection process.

Table 1: Comparison of existing tools based on the identified requirements.

	DR-1 Data Sources	DR-2 Analytics Methods	DR-3 User Wishes	DR-4 User Benefits	DR-5 Data Product
AI Canvas (Agrawal et al., 2018)	✓	✓	(✓)	-	-
Data Canvas (Mathis and Köbler 2016)	✓	-	-	-	-
Data Collection Map (Kayser et al., 2019)	✓	-	-	-	-
Data-Driven Business Value Matrix (Breitfuß et al., 2019)	(✓)	-	-	-	-
Data Innovation Board (Kronsbein and Mueller 2019)	✓	-	✓	✓	-
Data Insight Generator (Kühne and Böhmann 2019)	✓	✓	-	✓	-
Data Value Map (Nagle and Sammon 2017)	✓	✓	-	-	✓
Key Activity Canvas (Hunke et al., 2020)	-	✓	-	-	-
(Hunke and Schüritz 2019)	✓	✓	-	-	-

We checked the representations if they meet the five derived requirements, as shown in Table 1. As our review of previous research shows, no artifact has yet sufficiently solved the problem based on the identified requirements. Specifically, few visual tools incorporate the perspective of connecting data with the user challenges as well as conceptualizing the presentation of the data product.

5 Artifact Description – The Data Product Canvas

To overcome the gap of previous visual tools with data as a specific lense to support the collaborative development of data products, we developed the Data Product Canvas, which is shown in Figure 2. The DPC consists of seven elements: the name of the data product and the name of the customer addressed, highlighting the dyadic view of the provider and customer sphere. On a second level, the artifact consists of five vertical columns with the elements »data sources«, »data analytics« and »data product« in the provider sphere and »user benefits« and »pains and gains« in the customer sphere. For each element, an icon, a trigger question and illustrative examples are provided. The DPC can be used when an organization in an initiation phase aims to develop ideas for a data product. The canvas is used in a workshop setting with an interdisciplinary team of data scientists, domain experts and management.

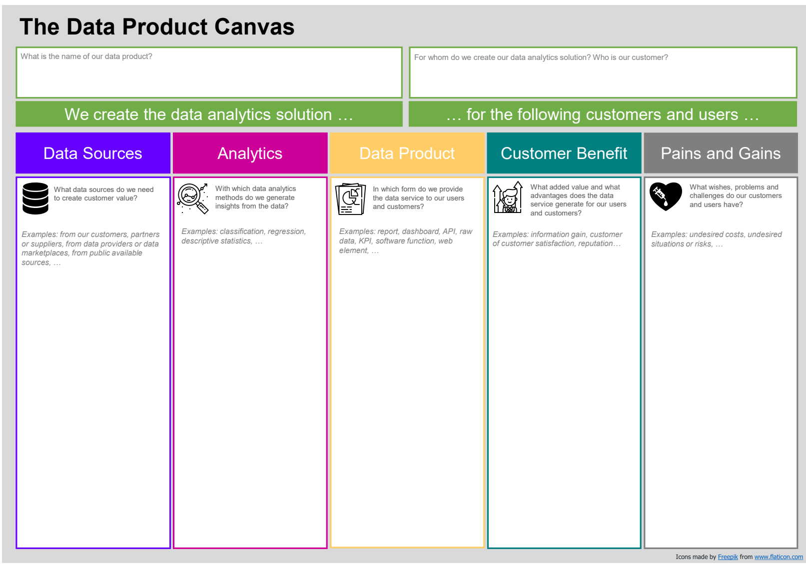

Figure 2: The Data Product Canvas

6 Artifact Evaluation

To complete our DSR project, we have to »observe and measure« (Peffers et al., 2007) how well our artifact supports the design of data products. This involves comparing the objectives of our solution with the observed results from the usage of the artifact (Peffers et al., 2007). In order to do so, we used workshops as an evaluation method (Thoring et al., 2020) to observe the usage of the artifact in cases of idea generation for data-driven business models. We have carried out four workshops with company representatives who are involved in ongoing processes of identifying and concretizing opportunities for data-driven business in their respective companies. Workshop attendance was between 6 and 18 participants;

group work in workshops was carried out in groups of 3-6 participants. Each workshop serves as a case for studying the Data Product Canvas in this paper. Table 2 gives an overview of the evaluation settings, describing the participants, duration and date of each workshop.

Table 2: Overview of evaluation settings of the Data Product Canvas.

Case	Description of participants	Number of Participants	Duration	Date
A	Representatives from green technology firms (e.g., general managers, engineers, innovation managers)	14 participants (4 groups of 3-4 participants each)	~60 min	Mar. 2019
B	Product, innovation, R&D manager and data scientist from an engineering company	6 participants (one group)	~120 min	Aug. 2019
C	IT-manager, data scientist and domain experts from a manufacturing company (e.g., quality, supply chain management or manufacturing)	11 participants (3 groups of 4-6 participants each) [1]	~60 min	Oct. 2019
D	Representatives from green technology firms (e.g., innovation, engineering, management)	18 participants (3 groups of 6 people)	~120 min	Feb. 2020

In order to increase the validity of the evaluation, we used data from different evaluation methods within the workshops, thus facilitating data triangulation: *(i) Observations and notes*: We were taking field notes during workshop, observing and documenting the participants' behavior and their interaction with the artifact. *(ii) Interviews and group discussion*: Participants were asked feedback questions directly after the workshop about the usefulness and ease of use. *(iii) Pictures*: We have documented the outcome (i.e., the filled canvas) of each workshop through pictures, thus enabling a content analysis of the developed ideas. The goal of each workshop setting was to conceptualize an idea for a data product. An initial idea was already provided in each case by the organization beforehand. In cases A, B and C the available data sources were already collected in a prior workshop. In each case, one researcher introduced the canvas and gave initial instructions, whereas a second researcher was observing the participants and taking notes.

[1] Workshops were conducted consecutively; two participants participated in all three workshops.

Overall, the DPC was perceived as useful by all groups and participants. An IT-manager in evaluation case C stated that the canvas was very effective to describe a data use case within a one-hour meeting. He didn't expect to be so fast. A participant in case A mentioned that this representation helps to organize the problem: »You see very quickly where to focus: What do you want? What does the customer want?« (participant in case A, group 2). Furthermore, identifying the user was perceived as a necessary but challenging task: »It took us quite a long time to figure out who our customers were, only then could we continue with the right elements [of the canvas]« (participant in case A, group 2). A data scientist in case C reported after the workshop that they are already using the canvas in their daily work in collaboration with other departments. Similarly, the organization of case B is considering including the canvas into their portfolio of innovation tools.

We have observed different sequences, how the participants filled out the canvas fields. For instance, one group in case A started with the data sources and ended with thinking about what they have to analyze (referring to »Analytics« column). Participants also noted that it was difficult to decide with what column to start. The majority of groups started from the left (»Data Sources«). This approach of using the canvas seems intuitive although no specific starting point was intended through the design. On the other hand, we have observed that participants found it easier to generate a data product idea when starting from the user perspective. Reflecting on all four evaluation settings, we derived the hypothesis that thinking about pains and benefits should be one of the first steps. Thus a further improvement of the canvas should provide guidance where to start.

We have also observed some termination problems: The difference between the category »Benefit« and the category »Pains and Gains« was not clear for several participants in all four cases. There was, for instance, the feedback from one participant that is was not clear what to fill into the column »Benefit«, as the information was in their perception already included in »Data Product« or »Pains and Gains«. Thus, a further improved version of the canvas and workshop format should further clarify those two concepts.

7 Conclusion

This paper presents the Data Product Canvas, a theory-inspired artifact based on requirements derived from literature. We have evaluated the usefulness and ease of use through several workshops with organizations. Overall, our evaluations show that the Data Product Canvas is well perceived, usable and of benefit for organizations and interdisciplinary teams that are initiating a data-driven innovation. The canvas design is the main contribution of this study. Furthermore, we consider the presented artifact as an additional contribution to the knowledge base in the field of data-driven business models and data product development.

Based on the results and contributions of this study, we see a broad range of opportunities for further research. *First*, the artifact could be further evaluated using quantitative measurement instruments. *Second*, further studies could combine the Data Product Canvas with other visual representation, where on the one hand the DPC could provide valuable input for other tools such as the Business Model Canvas (Osterwalder and Pigneur, 2010), or on the other hand, other tools provide information and input for the DPC, such as the Data Collection Map (Kayser et al., 2019) or the Value Proposition Canvas (Osterwalder et al., 2014); and overall contributing to a toolbox for developing data-driven services (Fruhwirth et al., 2020). *Third*, further research could also derive different characteristics for each dimension of the DPC, serving as examples and creativity support during exploration and ideation workshops. *Forth*, further research could have a deeper look at the mental process and the sequence of filling out the fields of the canvas. *Fifth*, further research could also study the role of the canvas as a boundary object and how it facilitates shared understanding between different stakeholders.

This research has two limitations: *Firstly*, the DPC evaluation is not comparative; we, therefore, cannot state whether or how much it is better than any other artifact for supporting the development of data products. On the other hand, the present evaluations have high ecological validity, as they supported exactly the target group in their ongoing tasks, namely company representatives responsible for identifying data-driven opportunities, and developing them in their respective companies who participate in the workshops because this is currently a task for them. *Secondly*, a large part of the workshop evaluation is based on observations and hence the results might show a bias towards the expectation of the researchers, who are also the designers of the canvas, that the intervention works (confirmation bias).

Acknowledgements

The research based on this paper has received funding from the Austrian COMET Program - Competence Centers for Excellent Technologies - under the auspices of the Austrian Federal Ministry of Transport, Innovation and Technology, the Austrian Federal Ministry for Digital and Economic Affairs and by the State of Styria. COMET is managed by the Austrian Research Promotion Agency (FFG).

References

Agrawal, A.; Gans, J.; Goldfarb, A. (2018): A Simple Tool to Start Making Decisions with the Help of AI. In Harvard Business Review Online. Available online at https://hbr.org/2018/04/a-simple-tool-to-start-making-decisions-with-the-help-of-ai.

Augenstein, D.; Fleig, C.; Dellermann, D. (2018): Towards Value Proposition Mining. Exploration of Design Principles. In ICIS 2018 Proceedings.

Bertoncello, M.; Camplone, G.; Husain, A.; Möller, T. (2018): From buzz to bucks – automotive players on the highway to car data monetization. McKinsey Center for Future Mobility.

Breitfuß, G.; Fruhwirth, M.; Pammer-Schindler, V.; Stern, H.; Dennerlein, S. (2019): The Data-Driven Business Value Matrix. A Classification Scheme for Data-Driven Business Models. In Proceedings of the 32nd Bled eConference.

Chen, Y.; K.reulen, J.; Campbell, M.; Abrams, C. (2011): Analytics Ecosystem Transformation: A Force for Business Model Innovation. In 2011 Annual SRII Global Conference.

Davenport, T.H.; Kudyba, S. (2016): Designing and Developing Analytics-Based Data Products. In MIT Sloan Management Review 58 (1), pp. 83–89.

Dremel, C.; Overhage, S.; Schlauderer, S.; Wulf, J. (2017): Towards a Capability Model for Big Data Analytics. In WI 2017 Proceedings, St. Gallen, pp. 1141-1155.

Fruhwirth, M.; Pammer-Schindler, V; Thalmann, S. (2019), "To Sell or Not to Sell: Knowledge Risks in Data-Driven Business Models", In 2019 Pre-ICIS SIGDSA Proceedings.

Fruhwirth, M.; Ropposch, C.; Pammer-Schindler, V. (2020): Supporting Data-Driven Business Model Innovation: Structured Literature Review on Tools and Methods. In Journal of Business Models 8 (1), pp. 7-25,

Glassberg Sands, E. (2018): How to Build Great Data Products (Harvard Business Review). Available online at https://hbr.org/2018/10/how-to-build-great-data-products.

Hartmann, P.M.; Zaki, M.; Feldmann, N.; Neely, A. (2016): Capturing value from big data – a taxonomy of data-driven business models used by start-up firms. In International Journal of Operations & Production Management 36 (10), pp. 1382–1406.

Hunke, F.; Engel, C.; Schüritz, R.; Ebel, P. (2019): Understanding the Anatomy of Analytics-Based Services. A Taxonomy to Conceptualize the Use of Data and Analytics in Service. In ECIS 2019 Proceedings.

Hunke, F.; Schüritz, R. (2019): Smartere Produkte durch analysebasierte Dienstleistungen – Ein methodisches Werkzeug zur strukturierten Entwicklung. In HMD 56 (3), pp. 514–529.

Hunke, F.; Seebacher, S.; Thomsen, H. (2020). Please Tell Me What to Do – Please Tell Me What to Do – Towards a Guided Orchestration of Key Activities in Data-Rich Service Systems. In DESRIST 2020 Proceedings.

Kayser, L.; Mueller, R.M.; Kronsbein, T. (2019): Data Collection Map. A Canvas for Shared Data Awareness in Data-Driven Innovation Projects. In 2019 Pre-ICIS SIGDSA Proceedings.

Kronsbein, T.; Mueller, R.M. (2019): Data Thinking: A Canvas for Data-Driven Ideation Workshops. In HICSS-52 Proceedings, pp. 561–570.

Kühne, B.; Böhmann, T. (2019): Data-Driven Business Models. Building the Bridge Between Data and Value. In ECIS 2019 Proceedings.

Kühne, B.; Zolnowski, A.; Bornholt, J.; Böhmann, T. (2019): Making Data Tangible for Data-driven Innovations in a Business Model Context. In AMCIS 2019 Proceedings.

Mathis, K.; Köbler, F. (2016): Data-Need Fit - Towards data-driven business model innovation. In Fifth Service Design and Innovation conference, pp. 458–467.

Moody, D.; Walsh, P. (1999): Measuring The Value of Information. An Asset Valuation Approach. In Proceedings of the Ninth European Conference on Information Systems.

Nagle, T.; Sammon, D. (2017): The Data Value Map. A Framework for Developing Shared Understanding on Data Initiatives. In ECIS 2017 Proceedings, pp. 1439–1452.

Osterwalder, A.; Pigneur, Y. (2010): Business Model Generation. A Handbook for Visionaries, Game Changers, and Challengers. 1st ed.: John Wiley & Sons.

Osterwalder, A.; Pigneur, Y.; Bernarda, G.; Smith, A.; Papadakos, P. (2014): Value proposition design. How to create products and services customers want. Wiley (Strategyzer series).

Peffers, K.; Tuunanen, T.; Rothenberger, M.A.; Chatterjee, S. (2007): A Design Science Research Methodology for Information Systems Research. In Journal of Management Information Systems 24 (3), pp. 45–77. DOI: 10.2753/MIS0742-1222240302.

Schneider, S.; Spieth, P. (2013), “Business Model Innovation. Towards an integrated future research agenda”, *International Journal of Innovation Management*, Vol. 17 No. 01, p. 1340001

Schüritz, R.; Farrell, K.; Wixom, B.; Satzger, G. (2019): Value Co-Creation in Data-Driven Services. Towards a Deeper Understanding of the Joint Sphere. In ICIS 2019 Proceedings.

Schüritz, R.; Satzger, G. (2016): Patterns of Data-Infused Business Model Innovation. In IEEE 18th Conference on Business Informatics, pp. 133–142. DOI: 10.1109/CBI.2016.23.

Seiberth, G.; Gründinger, W. (2018): Data-driven business models in connected cars, mobility services and beyond. BVDW Research. https://bvdw.org/datadrivenbusinessmodels/.

Tempich, C. (2019): Konzeption und Entwicklung von Data-driven Products/Datenprodukten. In Felden, C.; Zimmer, M.; Trahasch, U.; Haneke, U. Trahasch, S. (Eds.): Data Science. Grundlagen, Architekturen und Anwendungen. Heidelberg: dpunkt (Edition TDWI).

Thoring, K.; Mueller, R.; Badke-Schaub, P. (2020): Workshops as a Research Method: Guidelines for Designing and Evaluating Artifacts Through Workshops. In HICSS-53 Proceedings.

Wixom, B.; Schüritz, R. (2017): Creating Customer Value Using Analytics (MIT CISR Research Briefing, Volume XVII, Number 11, November 2017).